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Local Bias Among U.S.-based Hedge Funds

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Local Bias Among U.S.-based Hedge Funds

by

Mikhail Stukalo

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ACCEPTANCE

This dissertation was prepared under the direction of the *MIKHAIL STUKALO* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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This dissertation is dedicated to my daughter, Vasilisa, with the humble hope that she will also mention me when receiving her Nobel Prize.

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ABSTRACT

Local Bias Among U.S.-based Hedge Funds

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I examine local bias in hedge fund portfolio selection, using Section 13-F original and confidential holding filings. Using Coval and Moskowitz (1999) measure, I find that local bias is present among U.S.-based hedge funds. The holdings of funds are on average 20-67 km closer to hedge funds than the market. I also find that size and leverage of a company serve as determinants of local bias, with the preference of hedge funds for smaller and more levered local companies. I suggest an alternative model for assessment of local bias that yields results further supporting the hypothesis of the existence of local bias among hedge funds. I do not find a positive effect of local bias on performance. Moreover, in some periods I find a strong negative effect of local bias both on raw and risk-adjusted returns. I argue that these findings suggest that the origins of local bias should not be looked for in information asymmetry, and rather may be attributed to perceived informational advantage, flight to familiarity, and some endogenous factors of hedge fund locality.

INDEX WORDS: Hedge funds, Local bias, Location, Distance

I INTRODUCTION

Since the late 90s, the hedge fund industry demonstrated substantial growth in assets under management (AuM). According to BarclayHedge database[1], the total assets under management of hedge funds increased from $118 billion in 1997 to over $3 trillion as of the end of 2016. The importance of hedge funds as a large source of alternative returns drew attention of both practitioners and academia.

Academic literature is primarily focused on explanation of hedge fund returns based on market risk factors (Fung & Hsieh, 2004; Hasanhodzic & Lo, 2006). However, the decision-making process of stock selection by hedge funds is relatively uncovered. The notable exceptions are papers by Agarwal, Jiang, Tang, and Yang (2013), and Griffin and Xu (2009). The first paper looks into evidence provided by confidential stock holding reports about stock selection skills of hedge fund managers, and finds that holdings reported under confidentiality clause overperform other holdings by the same fund. The second paper compares stock picking skills of hedge fund managers to those of mutual fund managers and finds no significant difference between the skills of both groups. The key obstacle for the research on decision-making in stock selection by hedge funds is the secretive nature of the industry. Hedge funds are less regulated than traditional asset managers, and enjoy more relaxed reporting requirements than, for example, mutual funds (Agarwal et al., 2013).

From practitioners' point of view, hedge funds represent an important class of alternative assets. The popularity of hedge funds among large institutional investors, e.g. pension funds, endowments, etc., is based on a promise of delivering returns that have low correlation with the broader market. Therefore, hedge fund investments are expected to provide return diversification

[1] https://www.barclayhedge.com/research/indices/ghs/mum/Hedge_Fund.html

for institutional investors. I argue that the location of a hedge fund can introduce a source of under-diversification as it pertains to locality-specific risks. To illustrate this argument, let us suppose that Coca Cola[2] invests a large part of its pension plan's hedge fund allocation in Georgia-based hedge funds. If, in turn, Georgian hedge funds exhibit local bias, then regional-specific adverse events, e.g. natural disasters, change in local taxation regime, or economic downturns on regional level, may lead not only to an increase of Coca Cola pension plan liabilities due to financial stress to the company, but simultaneously to a deterioration of pension plan assets. Both the plan sponsor and the plan investments will be exposed to the same regional risk.

In this paper, I analyze local bias among U.S. hedge funds defined as a preference for stocks of companies located in geographic proximity to a fund. From existing academic literature we know that local bias is present among different groups of investors: individual investors (Ivković & Weisbenner, 2005; Seasholes & Zhu, 2010), institutional investors (Baik, Kang, & Kim, 2010), mutual funds (Coval & Moskowitz, 1999), and fund of funds (Sialm, Sun, & Zheng, 2014). However, there are no published papers that provide evidence of existence or absence of local bias in the hedge fund industry.

Moreover, there is no consensus in academia on the effect of local bias on performance. For instance, while Coval and Moskowitz (2001) and Baik et al. (2010) find positive effect of local bias on performance, Seasholes and Zhu (2010) argue that local bias does not lead to better performance. Shiller, Kon-Ya, and Tsutsui (1991) report negative effect of home bias on portfolio performance as a result of under-diversification.

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[2] According to Coca Cola 10-K filings for 2016 financial year, over $1.1 billion of $6 billion pension plan is invested in hedge funds (https://www.sec.gov/Archives/edgar/data/21344/000002134417000009/a2016123110-k.htm p.114)

My study is aimed at bridging the gap in academic literature by providing the evidence for existence of local bias among hedge funds, more specifically, U.S.-based hedge funds. I assess local bias in hedge fund portfolio selection using Coval and Moskowitz (1999) local bias measure. Also, I propose an alternative model of local bias that relies on comparison of divergence of stock portfolio weights in hedge fund portfolios from the weight of the same stock in portfolios of their peers. Both approaches provide robust evidence of the existence of local bias in hedge fund industry. Moreover, using Coval and Moskowitz (1999) measure, I analyze determinants of local bias, and come to the conclusion that consistent with Coval and Moskowitz hypothesis, hedge funds are more likely to exhibit local bias when investing in smaller stocks and stocks of companies that have higher level of leverage.

Next, I analyze performance of long equity portfolios sub-divided based on geographical proximity to a hedge fund. I do not find any positive effect of holding local portfolios on hedge fund performance, either raw or risk-adjusted. These results contradict findings of Coval and Moskowitz (2001). As a plausible explanation that needs to be thoroughly explored in further research, I suggest the effect of Regulation Fair Disclosure that was adopted in 2000, i.e. much later than the sample used in Coval and Moskowitz paper. Fair and simultaneous dissemination of material information may have changed the level of information asymmetry and done away with excess return associated with investments into local companies.

Finally, I suggest several plausible hypotheses of the causes of local bias. I argue that based on the results of my research the most plausible explanations are an endogenous nature of local bias linked to the industrial clustering in the U.S., and perceived informational advantage that does not generate excess returns in local stock portfolios, but creates a sense of familiarity of the target companies.

II LITERATURE REVIEW

Local bias is a part of a larger concept, “home bias puzzle”, defined as preference for domestic stocks over foreign stocks. In their seminal work, French and Poterba (1991) find that 98% of equity portfolios of Japanese investors, 94% of U.S. investors’ portfolios and 82% of British portfolios are held in domestics stocks. The proposed explanations included arguments of more favorable trading terms for domestic investors, e.g. taxes (Black, 1974), capital flow barriers (Stulz, 1981), and trade and transportation costs (Obstfeld & Rogoff, 2000). However, Tesar and Werner (1995) did not find empirical evidence of the effect of transaction costs on home bias. Another branch of literature that suggested plausible explanations for home bias argues that the source of the bias is an information asymmetry. For example, S. Orpurt (2002) finds that German research analysts predict earnings of domestic firms better than their foreign peers. In hedge fund research, Teo (2009) finds that funds investing in Asian stocks perform better if they have regional presence, either via headquarters or a local research office, than funds without an Asian presence. He also attributes this advantage to informational asymmetries.

Local bias is well documented among individual investors. Seasholes and Zhu (2010) find that in the period of 1991-1995 around 30% of stock holdings of households were stocks of companies located within 250 miles from the household. Similar results for the share of the local stocks in households’ portfolios (31%) are obtained by Ivković and Weisbenner (2005). However, the views on the effect of local bias on portfolio performance are contradictory between the papers. Seasholes and Zhu (2010) claim that performance of local stocks in households’ portfolios does not differ from performance of more distant stocks in the same portfolio. Ivković and Weisbenner (2005), on the other hand, find that local constituents of the portfolios overperform more distant stocks by 3.2% on average. They also suggest that returns are higher for local stocks that have some information asymmetries as evidenced by higher returns of stocks not included in S&P 500 index.

In the research of institutional money managers, local bias is reported by Baik et al. (2010). The authors analyze institutional holdings of local companies, i.e. what percentage of shares outstanding of a company is held by local institutional investors. They find that on average 3.2% of shares of companies are held by local institutional investors, defined as same-state managers. They also discover that when aggregated at manager's level, on average 8.2% of portfolio holdings of institutional investors is represented by a local firm. Moreover, this fraction differs for various types of institutional investors. Investment advisors have on average 10.3% of portfolio invested in local stocks, while for mutual funds this fraction is 8.2%. Furthermore, Baik et al. (2010) provide evidence that stocks that local institutional investors hold or trade earn higher excess returns around future earnings announcement dates than stocks held or traded by non-local institutional investors, suggesting an informational advantage of local investors.

In mutual funds, local bias is described in a seminal paper by Coval and Moskowitz (1999). They find that mutual funds in their cross-sectional analysis, invest in companies that are on average 160-184 kilometers closer to funds than the benchmark. In the follow-up paper, Coval and Moskowitz (2001) define local mutual funds as the ones that are located within 100 km from a firm, and find that local investments overperform more distant investments by on average 118 basis points per year after controlling for size, value and momentum factors. This allows the authors to suggest that local mutual funds possess superior information on local firms. However, it should be noted that the paper uses a sample of mutual fund returns for the period between 1975 and 1994. Therefore, the conclusions may be not relevant in the view of the

Regulation Fair Disclosure, adopted in August 2000 and requiring all publicly traded companies to disseminate material information to all investors simultaneously.

Finally, in the hedge fund field of studies, Sialm et al. (2014) documented local bias among funds of funds (FoF). From that perspective, local bias is defined as the difference between weights of local hedge funds[3] and non-local funds in the hedge fund portfolios of FoFs. The authors report that the local fund of funds overweigh local hedge funds by 15%. They find that local bias increases both raw and risk-adjusted performance of FoFs. For example, average return increases by 115 basis points for each unit of standard deviation of the local bias measure for a certain MSA. However, the authors also argue that local bias creates a local contagion effect when adverse events may be experienced by a large share of FoF's portfolio funds due to geographical crowding.

While local bias is well documented in various fields of research, its effect on performance is still a topic for discussion. As mentioned previously some authors (Baik et al., 2010; Coval & Moskowitz, 2001; Ivković & Weisbenner, 2005; Sialm et al., 2014) find positive effect of local bias on raw and risk-adjusted performance. These authors suggest that the excess return is earned due to information asymmetries. This point of view is also supported by the research on prediction accuracy by local analysts. For example, Malloy (2005) finds that geographically proximate U.S. analysts possess more information about local companies than analysts located further from firms. S. F. Orpurt (2004) finds higher prediction accuracy among local analysts in Europe, and Bae, Stulz, and Tan (2008) makes similar observations for local analysts in 32 non-U.S. countries. Another plausible explanation of higher returns on local

[3] Sialm et al. (2014) calculate weights from returns of FoFs and the hedge funds they hold, assuming that the return of a FoF can be viewed as a return of a portfolio of hedge funds. Locality is determined by location in the same administrative area (MSA).

investments is a better connection between local institutional investors and firms. Gaspar and Massa (2007) find that companies with higher ownership by local mutual funds have better corporate governance and shareholder protection policies. Kang and Kim (2008) provide evidence that block acquirers exhibit a strong preference for local firms, and are more likely to participate in post-acquisition activities than non-local investors. On the other hand, as mentioned earlier Seasholes and Zhu (2010) do not find positive influence of local bias on returns of individual investors. Shiller et al. (1991) analyze U.S. and Japanese investors behavior and conclude that home bias leads to under-diversification and overconfidence bias. Pool, Stoffman, and Yonker (2012) find that mutual fund managers that invest in companies in their home state (the state where they were born or raised) do not earn higher returns from these investments compared to investments in other states. However, they find that when home state and the state of the mutual fund location are the same, local investments generate higher raw and risk adjusted returns.

III DATA SOURCES AND VARIABLE CONSTRUCTION

III.1 Data Sources

The data on hedge fund portfolio holdings comes from Form 13F filings of institutional investment managers to SEC according to the Securities Exchange Act of 1934, Section 13(f). This act requires all institutions that have discretion over assets exceeding $100 million to report their holdings of Section 13(f) securities. These listed securities cover a large universe of U.S. traded stocks and some options on stocks. Therefore, from Form 13F we can learn about long position of institutional investors in most traded stocks of the U.S. issuers and some ADRs of foreign companies that are traded on U.S. stock exchanges. Institutional investors are required to report under Section 13(f) on quarterly basis.

In existing body of knowledge on local bias among institutional investors (e.g. Baik et al. (2010)), authors use Thomson Reuters Database as a primary source of data on institutional holdings. However, Thomson Reuters does not fully report hedge fund holdings. This argument comes from the fact that despite the requirement to report quarter-end holdings within 45 days after the end of the corresponding quarter, many hedge funds choose to use an exception to this rule that allows deferring disclosure of holdings by up to one year from the end of the mandatory 45-day period. According to Agarwal et al. (2013), 90% of confidential holdings of hedge funds in their sample were not reported by Thomson Reuters. Moreover, they find that on average over one-third of the total portfolio value of the hedge funds in their sample is reported in confidential filings. Often these positions represent stocks with a higher level of information asymmetry, and thus especially interesting for the analysis of local bias.

Another flaw of Thomson Reuters database, when it comes to hedge fund holdings, arises from vague classification of hedge funds in the database. Some hedge funds are reported by Thomson Reuters as Type 4 (“independent investment advisors”) entities, while a majority of hedge funds are classified as Type 5 ("others"). According to Thomson Reuters classification, the category "others" also includes pension funds, endowment funds, etc. As a result, this all-encompassing category becomes the largest category in the database, and significantly encumbers the analysis of hedge funds using Thomson Reuters database.

In order to address the aforementioned flaws, I use the updated database from Agarwal et al. (2013)[4]. The database includes original and confidential Form 13F filings of 1,419 hedge funds from 1999 to 2012. From SEC EDGAR website, I obtain unique postal addresses of the hedge funds in the sample[5] .

According to the Securities Exchange Act of 1934, Section 13(f), foreign institutional investment managers that hold more than $100 million worth of Section 13(f) securities are required to report their holdings to the SEC. However, this requirement covers only the U.S. traded securities. Therefore, assuming that the main investment focus of foreign investment managers may be outside of the U.S., I restrict my analysis only to U.S.-based hedge funds. After excluding hedge funds with foreign postal addresses and investment managers that have a majority of business in traditional asset management as opposed to hedge fund business, the resulting database contains quarterly holdings of 1,173 U.S.-based hedge funds. Following Coval and Moskowitz (1999), I exclude one fund from my sample that is located in Alaska. Therefore, the resulting sample consists of 1,172 funds.

Although Section 13(f) securities contain some of the options on the U.S. stocks, I restrict my analysis only to stocks. First, the list of Section 13(f) derivatives does not represent the

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[4] I am grateful to Dr. Vikas Agarwal and Hoglin Ren for providing access to the database

[5] The addresses were obtained from http://www.edgarcompany.sec.gov/servlet/CompanyDBSearch?page=main In the cases where fund addresses were missing, I searched for the address via Google search.

majority of the universe of structured products that hedge funds may use to express their investment views. Second, the reporting does not include the strike price and the expiration date of the option contracts. Therefore, it is impossible to calculate neither the portfolio weight nor the return of the option holdings. Finally, combining option contracts and stocks would be inaccurate, as by the nature of the option contract, the holder of the contract may choose not to exercise it foregoing the paid premium for the option. Whereas holding stocks in the portfolio creates an exposure to the stock price movements for the whole invested amount. I also exclude ADRs of non-U.S. companies from the sample of portfolio companies. The first reason for that is the scope of my research. I analyze local bias manifestation within the country, not a general home bias effect. The second reason is the fact that U.S. hedge funds are not required to report their holdings in non-U.S. stocks that are acquired on foreign stock exchanges. Therefore, inclusion of ADRs would bias the sample of foreign stock holdings. Further, to eliminate the possible effect of outliers and following Coval and Moskowitz (1999) and Pool et al. (2012), I exclude stock of companies located in Hawaii and Puerto Rico.

[Insert Figure 1*]*

From CRSP database, I obtain postal addresses for all portfolio companies in the sample. Through Google Maps application program interface (API), I collect geographical coordinates (latitude and longitude) of hedge funds and their portfolio companies.

The geography of U.S. hedge funds demonstrate a pronounced clustering around large financial centers: New York, San Francisco, Boston, Chicago, etc. This fact can be explained by both easier access to capital and better access to talent that hedge funds can enjoy in larger and more economically developed regions. In my sample, 43% of hedge funds are located in the state of New York, 14% in California and 9% in Connecticut. Some states are clearly unpopulated when it comes to the investment advisers targeting absolute return. For example, the only fund from Vermont in my sample is Champlain Investment Partners. The firm has over 20 years of experience, over $7.5 billion dollars under management, and focuses on mid- and small-cap investments in value stocks.

[Insert Table 1*]*

Finally, from CRSP database I obtain information on prices as of the month end (PRCCM), monthly total return (TRT1M), number of shares outstanding at the end of a quarter (CSHOQ), as well as quarterly data for calculation of book value of shareholders' equity: Shareholders' Equity – Total (SEQQ), Deferred Taxes and Investment Tax Credit (TXDITCQ), and Preferred/Preference Stock (Capital) – Total (PSTKQ). Fundamental and price data are matched with the sample using unique company identifiers in CRSP (LPERMNO).

III.2 Variable construction

In this paper, I use two alternative measures of local bias. The first measure (*LB*) is analogous to the one by Coval and Moskowitz (1999). I calculate weights of stocks in hedge fund portfolios and compare them to the market weights. Market weight is calculated as the share of a company's market capitalization in the total market capitalization of all CRSP stocks for the quarter. The difference between the market weight and the actual weight is scaled by the ratio of the distance from the fund to the portfolio company, and the market cap weighted mean distance from the fund to all companies in CRSP database:

$$LB_{f,t}^{i} = (W_{M,t}^{i} - W_{f,t}^{i})\frac{D_{f,t}^{i}}{D_{f,t}^{M}} \tag{1}$$

where
$LB_{f,t}^{i}$ *is the local bias measure for stock i in portfolio of fund f in time t*
$W_{M,t}^{i}$ *is the market weight of stock i in portfolio in time t*
$W_{f,t}^{i}$ *is the weight of stock i in portfolio of fund f in time t*
D_{f}^{i} *is the distance between fund f and company i*
$D_{f,t}^{M}$ *is the market cap weighted mean distance between fund f and all companies in CRSP database*

The alternative local bias measure is based on the assumption that hedge funds, unlike mutual funds, usually do not track any certain benchmarks when making investment decisions, but rather represent a class of assets known as 'absolute return'. Even in cases of the so-called 'closet indexing,' where a hedge fund allocates a substantial portion of its portfolio to the assets that have high exposure to the broader market risks, the severity of the 'closet indexing,' as well as the composition of the tracked market indices may significantly differ from fund to fund. I argue that despite known biases inherent for this approach (Fung and Hsieh (2004)), a more economically significant way to define the local bias among hedge funds is as a divergence of a stock weight in a fund's portfolio from the average weight of the same stock in portfolios of others funds. This measure (*Delta Weight*, $\Delta W_{f,t}^{i}$) is similar to the one used by Pool et al. (2012). From this point of view, we can conclude that there is a local bias if there is a negative relation between the difference in weights of local stocks compared to the average weights in the sample, and the distance between the funds' and the portfolio companies' headquarters.

Another significant difference of the approach taken in my paper from the methodology used by some other authors (e.g. Baik et al. (2010)), is that I avoid using states as qualifiers for the locality of the holdings. From Figure 1 we can see that although hedge funds are clustered around large cities, this clustering is not necessarily defined by state borders. For example, some funds that are located in Connecticut or New Jersey may be much closer to companies located in New York city than some funds from the state of New York. Moreover, portfolio companies in Iowa are much closer, and hence can be viewed as 'more local,' to funds in Illinois than to funds in California. Taking the aforementioned considerations into account, I calculate the divergence of funds' holdings from the average weight in the sample as:

$$\Delta W_{f,t}^{i} = W_{f,t}^{i} - \overline{W}_{xf,t}^{i} \quad , \tag{2}$$

where
$\Delta W_{f,t}^{i}$ *is the divergence of the weight of stock i in portfolio of fund f in time t*
$W_{f,t}^{i}$ *is the weight of stock i in portfolio of fund f in time t*
$\overline{W}_{xf,t}^{i}$ *is the average weight of stock i in time t in portfolios of all funds in the sample that hold stock i, except fund f, calculated as:*

$$\overline{W}_{xf,t}^{i} = \frac{\sum W_{t}^{i} - W_{f,t}^{i}}{N-1}, \ \textit{if } N>1$$

$$\overline{W}_{xf,t}^{i} = 0, \ \textit{if } N=1$$

Some funds in the sample invest substantial portions of their portfolios in exchange traded funds (ETFs) and mutual funds, which can be viewed as a type of 'closet indexing'. I argue that investments in ETFs cannot be considered as expression of existence or absence of the local bias. Therefore, I use values of investments in ETFs and mutual funds for calculation of portfolio weights, but then exclude these investments from the analysis of the effect of the distance on the over- or underweighting of stocks in hedge fund portfolios.

Using geographical coordinates of the hedge funds and their portfolio companies in the sample, I calculate distances between each fund and each company in its portfolio. The distances are calculated between the head offices of funds and portfolio companies. Some funds may have several offices in different parts of the country. In addition, there are companies, especially the large ones, that have numerous production and distribution facilities not only in the U.S., but also abroad. However, I choose to restrict the calculation of distances to distances between headquarters following Baik et al. (2010) approach and taking into account findings of Kang and Kim (2008), who conclude that headquarters provide critical decision-making information to investors, while branches and divisions do not.

Coval and Moskowitz (1999) report the distance measure formula that does not correctly account for the spherical shape of the Earth. As the result, using this formula, calculations of short distances roughly correspond to real distances between geographical locations. However, for longer distances, e.g. over 100 km, the Coval and Moskowitz (1999) distance measure formula produces significant errors (see Appendix A). Following Alam, Chen, Ciccotello, and Ryan (2014), I calculate distance between a hedge fund and a portfolio company using spherical law of cosines as:

$$Distance_{f,i} = r \times \arccos\left[\sin(lat_f)\sin(lat_i) + \cos(lat_f)\cos(lat_i)\cos(long_f - long_i)\right] \quad (3)$$

where
f, i denote a fund and a portfolio company respectively
long, lat - longitudes and latitude respectively (measured in radian)s;
r - radius. For calculation of distance between geographical coordinates, the radius of the Earth ≈6,378km.

I use Size, Book-to-Market, Momentum, and Leverage as control variables in my model to assess influence of the market capitalization and value characteristics on the divergence of portfolio weights, as well as to analyze the determinants of local bias. I calculate Size as a natural logarithm of Market Capitalization. Market Capitalization, in turn, is calculated as a product of the stock price at the end of the quarter and the number of shares outstanding.

Momentum is calculated as cumulative return for 4 quarters preceding the quarter of observation. Leverage is calculated as the ratio of total debt to total assets of the company. I calculate Book-to-Market using the following approach:

$$Book - to - Market = \frac{\mathrm{SEQQ} + \mathrm{TXDITCQ} - \mathrm{PSTKQ}}{\mathrm{CSHOQ}} \mathrm{PRCCQ} \tag{4}$$

where

SEQQ - shareholders' equity;

TXDITCQ - deferred taxes and investment tax credit;

PSTKQ - preferred stock (Capital);

CSHOQ - shares outstanding at the end of the quarter;

PRCCQ – closing price at the end of the quarter.

All data for *Size, Momentum, Leverage*, and *Book-to-Market* calculations is obtained from CRSP database, Fundamentals Quarterly.

I also calculate end of the quarter *Portfolio* of each fund as the sum of products of the number of shares and the closing price at the end of the quarter for each stock in a hedge fund's portfolio. It should be noted that the disclosure standards require funds to report only long positions in listed Section 13(f) securities. Also, as stated above, I restrict my analysis only to stocks, hence excluding long option positions. Therefore, *Portfolio* represents solely the total value of the long equity positions of a fund.

[Insert Table 2*]*

IV LOCAL BIAS IN HEDGE FUND PORTFOLIO SELECTION

IV.1 Presence of local bias in hedge funds

I start my analysis by comparing weights of stocks in hedge fund portfolios with the market weights of these stocks. The analysis is analogous to the one performed by Coval and Moskowitz (1999) with the exception that they used cross-sectional data in their paper, while I use the full longitudinal sample for the period 1999-2012. Distances from the funds to market portfolios are calculated in two different ways: as an arithmetic mean of distances, and as a mean weighted by market capitalizations of companies in a certain quarter. Then I compute mean distances from funds to all of its portfolio companies. This measure within a fund is calculated as weighted by values of the long equity positions both for *Equal* and *Value* case. On funds level I perform aggregation using equal weights for *Equal* scenario and weighted by long equity portfolio size for *Value* option. This way I obtain measures similar to Coval and Moskowitz (1999) *Equal-Equal, Equal-Value,* etc. Finally, I calculate mean distance across several observation quarters. Hence, the formulae for the local bias measures look as follows:

$$
\begin{aligned}
&LB(Equal - Equal) \\
&= \frac{1}{TFI} \sum_{t=1}^{T} \sum_{f=1}^{F} \frac{\sum_{i=1}^{I} (D_{f,t}^{i}\ Value_{t}^{i})}{\sum_{i=1}^{I} Value_{t}^{i}} \\
&- \frac{1}{TFM} \sum_{t=1}^{T} \sum_{f=1}^{F} \sum_{m=1}^{M} D_{f,t}^{m}
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
&LB(Value - Equal) \\
&= \frac{1}{T} \sum_{t=1}^{T} \frac{\sum_{f=1}^{F} \left(\frac{\sum_{i=1}^{I} (D_{f,t}^{i}\ Value^{i})}{\sum_{i=1}^{I} (Value^{i})}\ Portfolio_{f,t} \right)}{\sum_{f=1}^{F} (Portfolio_{f}\,, t)} \\
&- \frac{1}{T} \sum_{t=1}^{T} \frac{\sum_{f=1}^{F} \left(\left(\frac{1}{M} \sum_{m=1}^{M} D_{f,t}^{m} \right)\ Portfolio_{f,t} \right)}{\sum_{f=1}^{F} (Portfolio_{f}\,, t)}
\end{aligned}
$$

$$LB(Equal - Value) = \frac{1}{TFI}\sum_{t=1}^{T}\sum_{f=1}^{F}\frac{\sum_{i=1}^{I}(D_{f,t}^{i}\ Value_{t}^{i})}{\sum_{i=1}^{I} Value_{t}^{i}} - \frac{1}{TF}\sum_{t=1}^{T}\sum_{f=1}^{F}\frac{\sum_{m=1}^{M}(D_{f,t}^{m}\ Market\ Cap_{t}^{m})}{\sum_{m=1}^{m}(Market\ Cap_{t}^{m})}$$

$$LB(Value - Value) = \frac{1}{T}\sum_{t=1}^{T}\frac{\sum_{f=1}^{F}(\frac{\sum_{i=1}^{I}(D_{f,t}^{i}\ Value^{i})}{\sum_{i=1}^{I}(Value^{i})}\ Portfolio_{f,t})}{\sum_{f=1}^{F}(Portfolio_{f}\ ,t)} - \frac{1}{T}\sum_{t=1}^{T}\frac{\sum_{f=1}^{F}(\frac{\sum_{m=1}^{M}(D_{f,t}^{m}\ Market\ Cap_{t}^{m})}{\sum_{m=1}^{m}(Market\ Cap_{t}^{m})}\ Portfolio_{f,t})}{\sum_{f=1}^{F}(Portfolio_{f}\ ,t)}$$

Coval and Moskowitz (1999) found that on average mutual funds in 1995 were closer to their holdings than to the market by 160-184 kilometers. However, as stated above, I argue that their distance measure yields inaccurate outcomes. My results provide evidence that hedge funds also exhibit local preference, investing in holdings that are on average 20-67 kilometers closer to them than the market. For non-NY based funds this number is higher: 40-92 kilometers. These results are statistically significant, with t-statistics for all cases high enough to soundly reject null hypothesis of the absence of the local bias.

[Insert Table 3*]*

Besides using different distance measure, my analysis differs from Coval and Moskowitz (1999) in another important aspect. In their 1999 paper, Coval and Moskowitz used a cross-sectional analysis for the data coming from 1995. The degree of the local bias can change with time. This point of view is supported by the dynamics of local bias measure in percents as in Table 3 plotted for various years in my sample. Interestingly, local bias drops in 2001-2002, which coincides with the adoption of Regulation Fair Disclosure. It increases sharply in 2008, during the financial crises, which may indicate flight to more familiar, local companies in the times of distress.

[Insert Figure 2*]*

IV.2 Determinants of local bias

Next, I test the hypothesis suggested by Coval and Moskowitz (1999) that the size and the leverage of portfolio companies affect local bias. Following Coval and Moskowitz, I calculate local bias measure using equation (1). *Size* is defined as natural logarithm of *Market Capitalization*. *Leverage* is calculated using quarterly data from CRSP database, and defined as the ratio of total liabilities to total assets of a portfolio company. I perform a linear regression analysis, where the dependent variable is *LB* measure from equation (1). To account for autocorrelation of the local bias measure I include lagged local bias as one of the independent variables. The regression has the form of:

$$LB_{f,t}^{i} = \alpha + \beta_1 LB_{f,t-1}^{i} + \beta_2 Size_t^i + \beta_3 Leverage_t^i + \varepsilon_{f,t}^{i} \tag{6}$$

The results of the regression analysis and standard errors of the coefficient (clustered on stock-fund and quarter level) are reported in Table 4. The signs of the regression coefficients are consistent with findings of Coval and Moskowitz (1999). Negative regression coefficient of *Size* suggests that smaller portfolio companies are located closer to hedge funds. However, when I exclude New York based funds, *Size* coefficient ceases to be statistically significant. I conclude that New York-based funds exhibit preference for smaller local stock. Both New York-based funds and funds from other states exhibit strong and statistically significant preference for local stocks with higher leverage. The results of the analysis suggest that the hypothesis of the information asymmetry, whether perceived or real, is plausible. Smaller companies with high leverage are associated with higher risk, lower transparency, and higher probability of financial distress. By investing in such companies, hedge funds may count on informational advantage arising from less transparency of portfolio companies.

[Insert Table 4*]*

IV.3 Alternative specification of the local bias

The Coval and Moskowitz (1999) approach to measuring local bias implies comparison between the actual holdings of funds and the market portfolio. However, hedge funds are notorious for holding concentrated stocks positions. In my sample, an average fund-quarter observation contains 106 stock names (compared to 5,943 stocks in market portfolio). Therefore, I suggest using an alternative measure as defined in equation (2) that compares weights of stocks in a hedge fund portfolio to the mean weight of the same stock in portfolios of other funds in a sample (*Delta Weight).*

I examine the difference in *Delta Weights* of stocks in funds' portfolios for various buckets of distance. Instead of using quintiles for defining the buckets, I opted for a more practical and economically sensible definition based on proximity. I divide stocks into the following groups based on the distance from a hedge fund: 0 to 100 kilometers, 100 to 500 kilometers, 500 to 1,000 kilometers, 1,000 to 3,000 kilometers, and over 3,000 kilometers. The practical reasoning of this division comes from the assumption that companies located within 100 kilometers from a fund can be view as local: the travel is short enough to be made by car, hedge fund managers and top-management of companies are likely to share the same social circles. The 500-km cut-off represents a distance typical for companies located in nearby states. The 1,000-km limit covers companies in the same geographical region, e.g. North-East of the U.S., while the distance of 3,000 km is approximately the distance from East to West Coast of the United States (see Appendix B).

Next, I calculate mean *Delta Weight* for each distance group in the sample.

[Insert Table 5*]*

The results of the sorting suggest a strong preference of hedge funds for local companies, located within 100 kilometers from a hedge fund, which is in line with findings of Coval and Moskowitz (2001). Furthermore, mean *Delta Weight* decreases with every next bucket of distance, suggesting negative effect of *Distance* on *Delta Weight*.

I use ANOVA test to assess statistical significance of the difference in mean *Delta Weights*. Bartlett test of homogeneity of variances results in K-squared = 52617, df = 3, p-value < 0.0001. Fligner-Killeen test of homogeneity of variances produces Chi-squared = 4560.7, df = 3, p-value < 0.0001. Hence, I conclude that the variances of observations among groups are homogeneous, and I can perform ANOVA test of mean differences. From the test, I conclude that there is a statistically significant difference in means of *Delta Weight* among *Distance* groups.

[Insert Table 6*]*

I analyze difference in means among particular groups using Tukey HSD test. To address the possible issue with heteroskedasticity of the observations, I augment the test with standard errors clustered on a stock-fund and a quarter level and corresponding p-values. From Tukey HSD test I observe the statistical significance of difference in mean *Delta Weight* for the first distance group (0 to 100 kilometers) and all other groups. Also, there is a statistically significant difference between means for second group (100 to 500 kilometers) and the most distant group (1,000 to 4,500 kilometers). For other groups, I cannot conclude that the difference is statistically significant.

[Insert Table 7*]*

The result of the sorting analysis support the hypothesis of the existence of the local bias among hedge funds in portfolio selection. The economic implication of the sorting analysis is a strong presence of the local bias for companies, located in the closest proximity from a hedge fund (0 to 100 kilometers), compared to more distant companies.

IV.4 Linear model of distance effect on stock weight divergence

I begin my regression analysis of the dependence of *Delta Weight* on *Distance* from considering a linear regression approach. My weight divergence measure, *Delta Weight*, is relative in its nature, as it represents the difference between the weight of a stock in a fund's portfolio and the mean weight of the same stock in portfolios of all other funds in my sample.

Therefore, for the regression analysis I transform the distance measure into a relative measure as $\frac{D_{f,t}^{i}}{\overline{D}_{xf,t}^{i}}$, where *D* stands for "distance" measured in kilometers, and the subscripts correspond to subscripts in equation (2). To address a strongly convex shape of the fitted function describing the relationship between the distance measure and *Delta Weight*, I further transform the distance measure by taking a natural logarithm.

I also introduce control variables to the regression. As a proxy for value vs. growth strategies, I use *Book-to-Market (BM)* ratio of the portfolio companies. I also control for the *Size* of portfolio companies, and for *Momentum* factor, defined as cumulative return in four preceding quarters. *Delta Weight* exhibits autocorrelation. To reflect this property of *Delta Weight*, I include lagged variable into the regression equation. The final model of the linear regression has the following formulation:

$$\Delta W_{f,t}^{i} = \alpha + \beta_1 \log(D_{f,t}^{i}/D_{xf,t}^{i}) + \beta_2 Size_t^i + \beta_3 BM_t^i + \beta_4 Momentum_t^i + \beta_5 \Delta W_{f,t-1}^{i} + \varepsilon_{f,t}^{\,i} \tag{7}$$

The regression results are presented in Table 8. Column 1 contains the outcomes of linear regression (7) applied to the full sample of stocks in the database. Column 2 reports regression results for the set of 1,000 largest capitalization stocks in CRSP database. The latter analysis works as a robustness check in the view of the fact that some stocks that funds hold in their portfolio can be described as 'unpopular', meaning that only a small number of funds hold them.

[Insert Table 8*]*

The OLS regression shows negative relationship between the distance measure and *Delta Weight*. In other words, the closer a company located to a hedge fund, the larger is the difference between the weight of this stock in the fund's portfolio compared to the mean weight of this stock in the portfolios of other hedge funds that hold the same stock. More specifically, every standard deviation of the distance ratio increases *Delta Weight* by on average 0.0134 percent, which is also economically significant given the average *Delta Weight* in the sample of 0.007 percent. The regression also gives an insight into the characteristics of portfolio companies of hedge funds. Regression coefficients indicate that hedge funds on average favor larger capitalization, value stocks.

Next I perform the same linear regression analysis for two sets of sub-samples. I divide observations based on the size of *Portfolio*. First sub-sample contains observations where the size of fund *Portfolio* is larger than the median *Portfolio* for that quarter. The second sub-sample contains *Portfolios* smaller or equal to the quarter median. The results presented in Table 9suggest that the local bias effect is stronger for smaller portfolios than for larger ones. I suggest two plausible explanations for this effect. First, smaller *Portfolios* can be more heavily invested in smaller companies without experiencing liquidity constrains. It is also supported by stronger negative effect of *Size* on *Delta Weight* in portfolios below median. The ability to invest in smaller companies, in turn, expands the universe of potential investment targets and allows expressing local bias by investing in local small-caps. The second plausible explanation is that smaller *Portfolios* are more likely to be more concentrated, which is represented by higher intercept term for the sub-sample of smaller *Portfolios*. Higher concentration, and hence lower diversification of the portfolio, may lead to investing more heavily into 'familiar' companies, catalyzing the local bias.

[Insert Table 9*]*

IV.5 Piecewise regression analysis

I further develop the linear model by considering a piecewise regression. First, I fit a generalized additive model and plot the fitted function (Figure 3). Visual inspection shows that the slope of the fitted line changes around $Log(D^i_{f,t}/D^i_{xf,t}) = 0$. I use zero as a breakpoint for the piecewise regression. The choice of zero as a breakpoint also has a practical sense, as it distinguishes between portfolio companies that are located closer to the fund of observation than on average to other funds in the sample and the companies that are located further away.

[Insert Figure 3*]*

The regression includes the same control variables as regression (7) and has the form of:

$$\Delta W^i_{f,t} = \alpha + \beta_1 \log(\frac{D^i_{f,t}}{D^i_{xf,t}}) + \beta_2 \max(\log\left(\frac{D^i_{f,t}}{D^i_{xf,t}}\right) - 0{,}0) + \sum_{n=3}^{5} \beta_n Controls + \beta_6 \Delta W^i_{f,t-1} + \varepsilon^{\,i}_{f,t} \tag{8}$$

The results of the regression analysis provide further evidence for the existence of local bias. The negative slope of the regression coefficient declines further by -0.0185, when $Log(D^i_{f,t}/D^i_{xf,t})$ is below zero, i.e. when the portfolio company is closer to the fund than on average to other funds. In this case, a decrease by one standard deviation of the relative distance measure increases stock weight divergence, *Delta Weight*, by 0.0289% compared to the increase by 0.0104% when the stock is further from the fund than from other funds on average. For the robustness check, I perform the regression analysis on the sub-sample of 1,000 largest capitalization stocks for each quarter in CRSP database. The regression yields similar results.

[Insert Table 10*]*

IV.6 Effect of local bias on portfolio performance

I explore the effect of local bias on performance of hedge fund holdings by constructing a local and a distant portfolio for each fund. The portfolio construction follows Coval and Moskowitz (2001). I define local portfolio as a portfolio of companies located within 100 km from a hedge fund. For each distance portfolio, I recalculate the weight of stocks by scaling actual weights by the weight of the local portfolio in the total *Portfolio* of the fund. Hence, the weights of stocks in each portfolio sum up to one. For example, if a hedge fund invests 40% equally in four local stocks, each stock will have 25% in the local portfolio.

I assume that funds hold the same weights of stocks in the next three months after the report date. Therefore, the assumption is that the reported number of stocks is the actual holdings of funds as of the end of the quarter. Filling portfolio weights forward partially addresses the problem of "window dressing" in 13F reports (Agarwal, Gay, & Ling, 2014), and can be considered a more conservative approach for performance analysis (Coval & Moskowitz, 2001).

Next, I calculate monthly returns of each distance portfolio for each fund in the sample. I notice that some funds do not have local portfolios as defined above. In order to avoid the bias in the database and to better address the question of comparison of local and distant returns, I exclude from the analysis fund-month observations where a fund does not have either local or distant portfolio holdings.

I report average annualized returns in Table 11. Monthly returns are multiplied by twelve and are averaged using equal weights and weighted by *Portfolio* size. To further explore difference in performance I report local and distant portfolio returns for various quintiles of local portfolio weights in the total *Portfolio* of a hedge fund.

[Insert Table 11*]*

Unlike Coval and Moskowitz (2001), I do not find superior performance of local portfolios. Moreover, in the period 1999-2005 as well in the full sample 1999-2012 local portfolios underperformed distant portfolios on average (using equal fund weights) by 2.59% and 0.90% respectively. The value weighted average performance was lower for local portfolios by 2.78% and 1.24% for the respective time periods. These results are statistically significant. As a plausible explanation of the difference between my results and those of Coval and Moskowitz, I suggest the adoption of Regulation Fair Disclosure. Coval and Moskowitz (2001) cite information asymmetry as the key explanation for better performance of local stocks. Apparently, with simultaneous information dissemination, the asymmetry may have disappeared. In such case, lower returns for local portfolios can be explained by introduction of additional risk associated with high geographical concentration of local portfolios.

In order to assess risk adjusted performance difference in local and distant portfolios, I calculate *Alphas* by fitting the data into linear factor models, namely the CAPM , Fama and French (1993) , and Carhart (1997) [6]. The factor models have the form of:

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[6] I obtain factors for Fama and French, and Carhart models from Kenneth R. French website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

$$R_i - R_f = \gamma + \sum_{n=1}^{N} Factors_n + \varepsilon_i \qquad (9)$$

The inputs for the regression models are monthly returns of local and distant portfolios averaged across funds using equal weights and weighted by fund *Portfolios*. I calculate monthly *Alpha* as an intercept term of the respective regression, and annualize it multiplying by 12. The results are presented in Table 12. Generally, local portfolios underperform distant portfolios also in terms of risk-adjusted returns, Alphas. The notable exception is risk-adjusted performance in 2006-2012, where local Portfolios overperform distant ones, and the difference in *Alphas* is statistically significant for Fama and French, and Carhart models. This may suggest that later in this decade smaller funds were able to extract valuable information on local companies better than larger funds. It also corresponds to the numerous findings in academic literature suggesting superior risk-adjusted performance of smaller funds compared to larger ones.

[Insert Table 12*]*

IV.7 Origins of local bias

I consider several plausible explanations for the existence of the observed local bias. These hypotheses can be divided into two groups: endogenous factors and information asymmetry.

I argue that endogeneity of local bias can manifest itself in the decision to open a hedge fund in a particular location close to an industrial cluster in which the hedge fund specializes. The geographical distribution of industries in the U.S. (e.g. Swann and Prevezer (1996)) makes this hypothesis plausible from practical point of view. For example, tech companies tend to have campuses in California, and more specifically in San Francisco area; large financial institutions are headquartered in the state of New York, etc. Hedge funds that specialize in certain industries may choose to open offices closer to the clusters of companies, operating in their focus industries. This choice may come from the easier access to talent, specializing in certain industries, or from easier access to financial resources that may also be industry specific, e.g. when investors into hedge funds have preferences with regard to industry focus of funds they invest into. There are some anecdotal examples that illustrate the hypothesis of industrial focus as a determinant of funds location. Artis Capital Management, a San Francisco-based hedge funds, focused on investments in tech sector. The proximity to portfolio companies allowed the fund to gain access to material information. It backfired in 2016 when the fund was charged with relation to insider trading and settled the case paying over $9 million in fines and penalties. However, anecdotal example, although shaping the “common wisdom”, cannot be use as a proof of the hypothesis. To assess the plausibility of this hypothesis, I perform the analysis of industrial attribution of hedge fund holdings. I select three states: New York, California, and Texas. First, these are the states with the large presence of hedge funds. In fact, in my sample, New York and California are the two largest contributors of the hedge fund information. Also, all three states are often perceived as states with pronounced industry clustering. New York is known for strong financial sector, California is famous for hosting the largest IT and biotech companies, and Texas is associated with the oil and gas industry. Table 13 reports 5 largest industries based on SIC major industry codes and on the data of entire CRSP stock universe for the period 1999-2012. The largest industries in these selected states correspond well to the common belief about industrial clustering in the U.S.

[Insert Table 13*]*

However, when I analyze the industrial attribution of hedge fund holdings by calculating portfolio weighted average stock weights of certain industries (Table 14), I conclude that New York-based funds do not exhibit industry focus corresponding to the industry clustering in the state. Financials are not among the top-5 industries by the portfolio weights of the funds based in the state of New York. Conversely, California-based funds invest heavily in electronics and computer equipment industries. Also, Texas-based funds have pipelines and oil & gas industries among the top-5 industries of portfolio investments. Therefore, the hypothesis of endogenous nature of local bias, caused by choosing the location of a hedge fund in proximity to industry clusters, may be valid for states other than New York.

[Insert Table 14*]*

Information asymmetry is often cited as an explanation of home and local bias. I argue that we should distinguish between perceived and actual information asymmetry. Hedge fund managers may perceive having an informational advantage about the local companies. Although Regulation Fair Disclosure of August 2000 requires simultaneous dissemination of material information by publicly traded companies to all investors, local investors may feel that they possess non-material (soft) information that gives them an edge over non-local investors. Local investors often share the same social circles with top-management of large local companies. The direct access to top-management in formal and informal settings may create a sense of possession of unique insights into the company's state of affairs.

My analysis of difference in raw and risk-adjusted performance between local and distant portfolios suggests that in the sample period, hedge funds were unable to capitalize on local stocks. This may serve as evidence that informational advantage is generally not present for local hedge funds.

The aforementioned informational advantage can also be perceived, i.e. hedge fund managers believe that they have access to important “soft” information that gives them an investment edge. The test of this hypothesis cannot be performed using available information on stock holdings by hedge funds.

Further research, including qualitative studies of hedge fund investment decision-making, may shed more light on the origins of local bias.

V DISCUSSIONS

V.1 Contributions

This paper contributes both to the academic body of knowledge and to business practice is several meaningful ways. First, it adds to the findings of Coval and Moskowitz (1999) with some notable differences. Coval and Moskowitz performed their analysis using a cross-sectional data from 1999. I argue that local bias changes depending on current legislative and economic conditions. I use longitudinal data from 1999-2012 and find that local bias, measured using Coval and Moskowitz approach fluctuated significantly. More specifically, the level of local bias dropped following 2000, which may be explained either by the change in market conditions (the dot-com crash of 2000), or by the change of the legislation (introduction of Regulation Fair Disclosure, Reg FD). Also, even despite the fact that Coval and Moskowitz (1999) distance measure underestimates larger distances, the results of my analysis using more correct distance measure shows that the effect of distance is much lower than it was reported for mutual funds. It may be the result of introduction of Reg FD and subsequent loss of attractiveness of local investments as a source of informational advantage. It also can be expected due to the nature of hedge funds. Unlike mutual funds, hedge fund can express their investment view by using short selling and financial derivatives. From this point of view, the fact that I find local bias by analyzing just long equity portfolios of hedge funds may be viewed as the most conservative approach and provide evidence that local bias actually exists among hedge funds.

Another academic contribution comes from development of alternative models for evaluation of local bias. I propose linear and piecewise regressions that describe the divergence of stock weights in hedge fund portfolios from mean weights in hedge fund industry. Coupled with relative distance measure, the models allow analysis of local bias in relative rather than absolute terms.

Finally, my research contributes to the conversation on effect of the local bias on performance, and through it, to the argument about presence or absence of information asymmetry that can be capitalized on by local hedge funds. Since publication of the seminal work by Coval and Moskowitz (2001), regulations and market conditions changed significantly to eliminate information asymmetry as a source of excess profit.

From a practical point of view, the research on local bias among hedge funds may be of use for investors in hedge funds. Local bias leads to concentration of risks on geographical level, which may lead to contagion of geography specific adverse events among local hedge funds. Coupled with documented local bias among funds of hedge funds such an event may send shock through the whole alternative finance sector in the area. This additional risk is not compensated for by higher returns. I do not find any positive difference between local and distant portfolio performance. Moreover, in some time periods local portfolios strongly underperform distant ones.

Some investors in hedge fund may have concentrated geographic risks on the liabilities side of their balance sheet. An example of such concentration is portfolios of regional pension funds investing for local work force, e.g. Teachers’ Retirement System of Georgia (TRSG) that manages retirement funds for school and higher degree educators. Investments into alternative assets, such as hedge funds, may look as an appealing instrument of risk diversification. However, the liabilities of TRSG depend on the level of school system financing, which in turn is dependent on economic conditions in the region. Investing with funds that exhibit strong local bias will concentrate geographical risk on the asset side of TRSG. Therefore, considering local bias when making asset allocation decisions will allow investors like TRSG to avoid risk concentration that is not compensated with higher returns.

V.2 Limitations and future research

The key limitation of my research arises from the specifics of hedge fund reporting under Section 13-F. Hedge funds use a wide range of financial instruments to express their investment views. Arguably, information asymmetry is more likely to manifest itself in case of negative rather than positive information. Companies are willing to report to the investment public good news. However bad news is likely to be shared reluctantly. The proximity to a company may allow obtaining "soft" information valuable to piece together adverse information about the company ("mosaic theory"). If information on the structure of short selling by hedge funds as well as information with detailed derivative position becomes available for academia, future research will be able to analyze local bias not only from long equity positions, but also from other sources of return.

Absence of detailed information on derivative holdings also distorts the picture of local bias in long equity portfolios. Funds may use some long equity positions not as an independent source of return, but as a hedge against adverse outcomes of derivative positions or as a part of complex derivative strategies, e.g. covered put or synthetic option positions. An ability to differentiate between pure long positions and positions related to derivatives would improve the correctness of the analysis of local bias. However, under current disclosure requirements, such information is not available.

Thirdly, disclosure of holdings under Section 13-F is required on management company level. Therefore, for funds pursuing multiple investment strategies or funds that besides hedge fund business have a substantial part of operations in other asset management businesses, researchers cannot accurately perform the analysis of the effect of funds strategies on local bias.

Although, it may be expected that equity funds have stronger local bias than, for instance, convertible arbitrage hedge funds.

Finally, local bias relates to a decision-making process in hedge funds. Although we can suggest hypotheses about the origins of the local bias, some of these hypotheses lay in the realm of behavioral finance. The hypothesis of endogeneity of hedge fund location selection and the hypothesis of perceived informational advantage are examples of such behavioral context. I suggested some ways to assess plausibility of these hypotheses. However, future research, perhaps qualitative or experimental in nature, is needed to explore local bias as a cognitive or an emotional type.

VI CONCLUSION

In this paper, I explore local bias among U.S.-based hedge funds. I find that local bias is present among hedge funds, although at lower level than it was reported in mutual fund domain. I also show that the size of a company and the level of leverage are determinants of local bias, with smaller and more levered companies representing more proximate part of hedge fund portfolios.

I also suggest an alternative measure based on stock weights in portfolios of hedge funds and distance between hedge funds and portfolio companies, where both weights and distance are measured in relative terms to the mean weight and distance of the same stock as relates to other hedge funds. I show that using these relative measures, we can model local bias through linear and piecewise regression. Also through the sorting analysis, I provide evidence of strong relative preference among hedge funds for local companies (closer than 100km).

Finally, I explore the effect of local bias on portfolio performance and find that local portfolios on average do not deliver better raw or risk-adjusted returns than distant portfolios. Moreover, in some instances the performance of local portfolios is lower than the performance of distant portfolios. These findings allow me to conclude, that the hypothesis of better access to company information from a local hedge fund is unlikely to hold.

APPENDICES

Appendix A: On distance measure

Coval and Moskowitz (1999) report the following formula for calculation of the distance between a mutual fund and a portfolio company:

$$d_{i,j} = \arccos\{\cos(lat_i)\cos(lon_i)\cos(lat_j)\cos(lon_j)$$
$$+\cos(lat_i)\sin(lon_i)\cos(lat_j)\sin(lon_j)$$
$$+\sin(lat_i)\sin(lat_j)\}2\pi r/360$$

I argue that the aforementioned formula does not take into account the spherical shape of the Earth. As the result, short distances are calculated fairly accurately, while longer distances are estimated incorrectly.

In my paper, I use the formula from Alam et al. (2014) that relies on spherical law of cosines, and is expressed as:

$$d_{i,j} = r \times \arccos\ [\sin(lat_i)\sin(lat_j) + \cos(lat_i)\cos(lat_j)\cos(lon_i - lon_j)]$$

Table A1 shows the result of application of spherical law formula (Column 9) and Coval and Moskowitz formula (Column 10) on three randomly chosen pairs of coordinates. As a benchmark (Column 11), I use the distance between these coordinates reported on the National Hurricane Center website[7].

[Insert Table A1]

[7] http://www.nhc.noaa.gov/gccalc.shtml

Appendix B: A sense of distance

In order to assess the reasonability of the chosen distance group, I obtain characteristic of administrative units from U.S. Census Bureau[8]. To better visualize the areas, I report the radius of a circle that has the same area as administrative units.

The chosen measure of locality (100km) approximately corresponds to 3-4 counties in the U.S. The cut-offs for distance groups (500 and 1,000km) can be compared to the areas of 2 and 4 "average" states, respectively.

[Insert Table A2]

[8] https://www.census.gov/support/USACdataDownloads.html

Appendix C: Tables and Figures

Figure 1:Geographical distribution of the sample

On this figure, red dots represent geography of hedge funds in the sample. Blue dots – geography of their portfolio companies. X- and Y- axes represent longitude and latitude respectively.

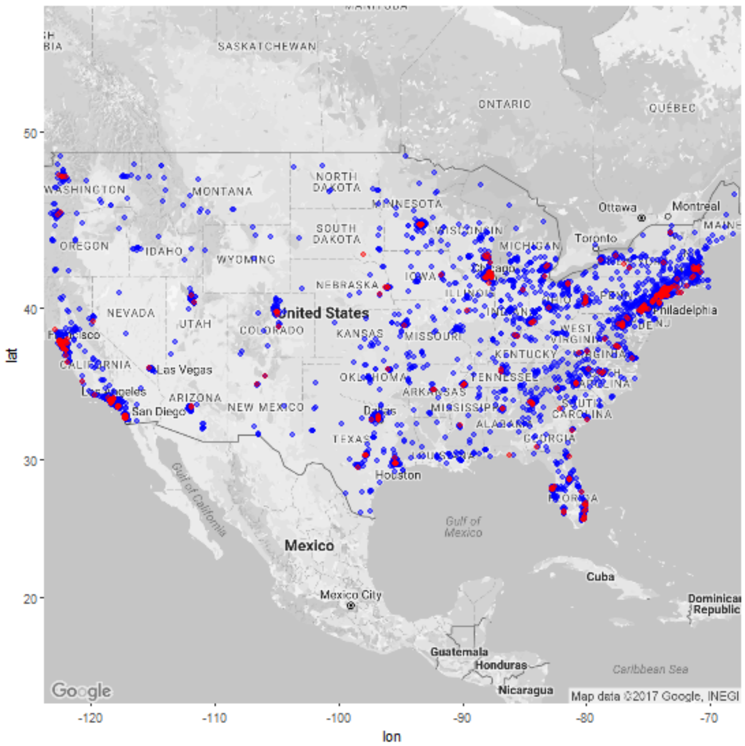

Figure 2: Dynamics of the local bias

This figure shows dynamics of Local Bias measures in percent. The averaging is performed as in *Equal-Value* case of Table 3.

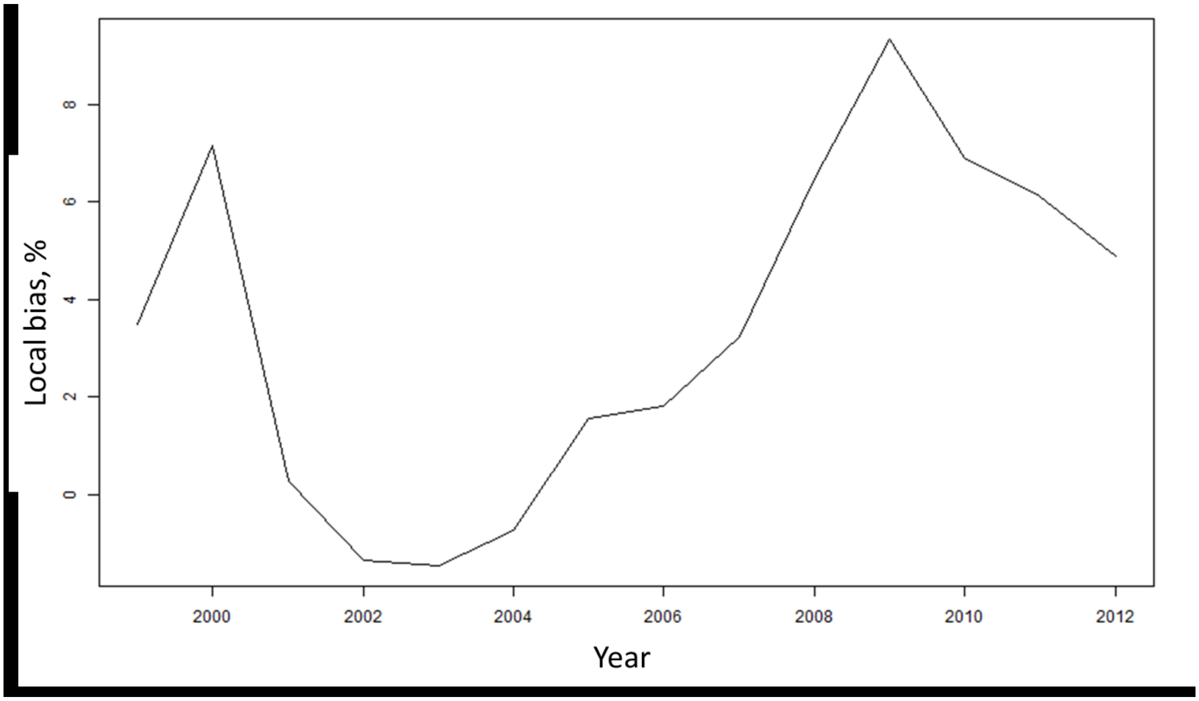

Figure 3: GAM model

This figure shows the results of fitting of generalized additive model (GAM). Solid line represents the fitted results. Dashed lines depict 95% confidence interval.

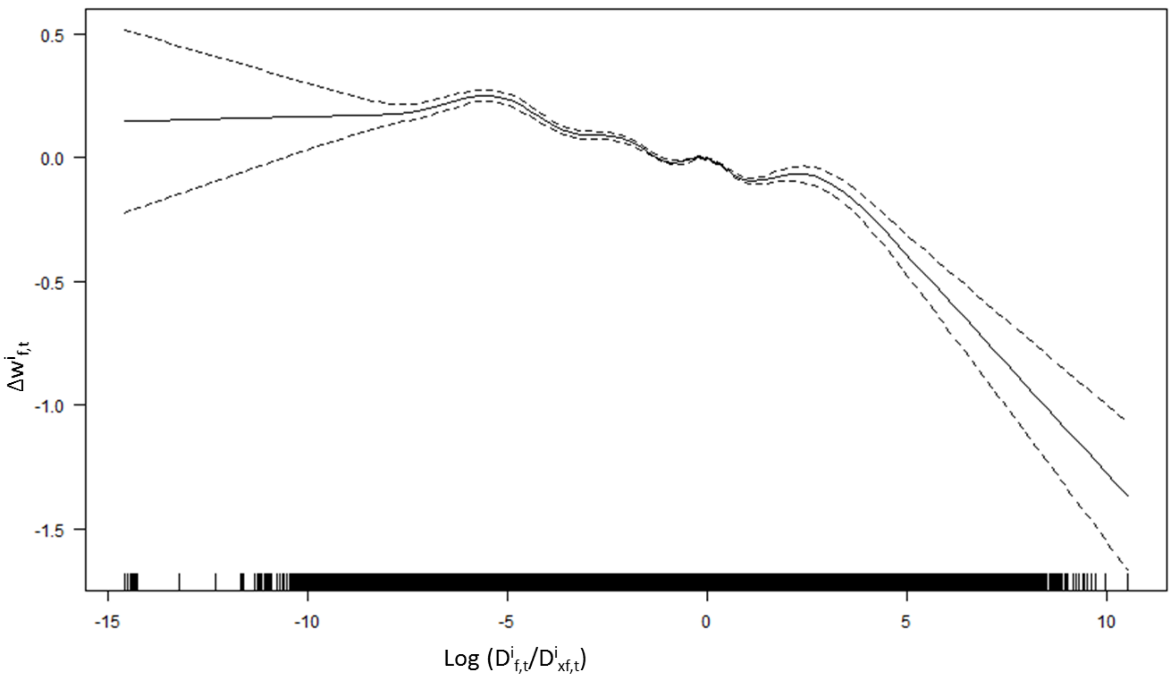

Table 1: Geographical distribution of the sample

This table reports number of hedge funds for each state in the sample. In total, the sample includes quarterly observations for 1,166 funds in the period between 1999 and 2012.

State	N of funds
New York	505
California	169
Connecticut	106
Massachusetts	76
Texas	48
Illinois	46
Pennsylvania	27
Florida	26
New Jersey	26
Minnesota	18
Virginia	15
Washington	13
Georgia	11
Colorado	9
Maryland	9
North Carolina	9
Ohio	9
Tennessee	6
Wisconsin	5
Nebraska	4
Delaware	3
Michigan	3
South Dakota	3

State	N of funds
Alabama	2
Arizona	2
Arkansas	2
Indiana	2
Kansas	2
Nevada	2
New Mexico	2
Oklahoma	2
South Carolina	2
Utah	2
Iowa	1
Kentucky	1
Mississippi	1
Oregon	1
Rhode Island	1
Vermont	1
Total	**1,172**

Table 2: Summary statistics

This table shows the summary statistics for the key variables used in the analysis. The sample period is from first quarter of 1999 to fourth quarter 2012. The portfolio holdings in the sample include confidential filings. *Distance* is a distance in hundreds of kilometers between the office of a hedge fund and the headquarter of a corresponding portfolio company. *Market Distance* is distance in hundreds of kilometers to all equities in CRSP database, weighted by market capitalization. *Portfolio* is the sum of values of all long stock positions of a fund as of the end of the quarter. *Weight* is the percentage of a long stock portfolio allocated by fund *f* to the shares of company *i* in a given quarter of 13-F Filing. *Weight excl.* is weight of stock *i* in portfolios of funds other than fund *f*. *Delta weight* is the difference between *Weight* and *Weight excl*. *Return* is the total quarterly return of stock *i* for quarter *t*. *Market Cap* is a market capitalization of portfolio company *i* as of the end of quarter *t-1*. *Size* is a natural logarithm of *Market Cap*. *Book-to-Market* is the ratio of book value of common equity per share to *Price*. *Momentum* is a cumulative return for four quarters preceding the quarter of observation. *Leverage* is a ratio of total liabilities to total assets. *Return, Book-to-Market, and Momentum* are winsorized at 1% and 99%. *Distance, LB, Portfolio, and Weight* minimum values that appear as zero are the results of rounding. Actual minimum values are small, but differ from zero.

	N	**Mean**	**Median**	**St. dev**	**Min**	**Max**
Distance measure ('00 km)						
Distance, D^{i}_{f}	2,692,612	18.144	15.252	13.802	0.000	44.571
Market distance, $D^{M}_{f,t}$	2,692,612	18.330	17.115	4.321	12.164	29.774
Portfolio size (mln $)						
Portfolio $_{t}$	2,704,047	5,143.042	937.176	11,272.994	0.000	89,605.436
Local bias						
LB $^{i}_{f,t}$	2,692,612	-0.759	-0.044	3.633	-287.086	9.754
Weights ,%						
Weight, $W^{i}_{f,t}$	2,692,612	0.904	0.151	2.973	0.000	100.000
Weight excl., $W^{i}_{xf,t}$	2,692,612	0.897	0.663	1.103	0.000	100.000
Delta weight, $\Delta W^{i}_{f,t}$	2,692,612	0.007	-0.297	3.035	-100.000	100.000
Portfolio investments						
Return $^{i}_{t}$ (%)	2,679,017	3.583	2.813	22.973	-56.360	88.889
Market Cap $^{i}_{t}$ (mln $)	2,548,838	18,296.668	2,662.355	46,485.425	0.281	626,550.353
Size $^{i}_{t}$	2,548,838	7.975	7.887	2.024	-1.270	13.348
Book-to-Market $^{i}_{t}$	2,646,677	0.553	0.449	0.453	-0.271	2.599
Momentum $^{i}_{t}$	2,598,194	17.760	9.730	56.970	-79.575	295.496
Leverage $^{i}_{t}$	2,678,033	0.566	0.561	0.283	0.000	37.308

Table 3: Test of local equity preference

This table reports the results of test of local equity preference for 1,172 hedge funds for the period 1999-2012. Distance measures are averaged on fund level using *Equal* weights, or weighted by the size of the long equity portfolio (*Value*). On portfolio firm levels the distances are averaged using *Equal* weight, or weighted by market capitalization of a company (*Value*). *Distances* and difference in distances (*Diff.*) are measured in kilometers. *Local Bias, %* is calculated as *Diff/Distance to Holding*. Last column reports t-statistics for difference in means between distance to *Holding* and *Distance to Market*. The table reports results for the full sample of funds and for the sub-sample excluding funds based in the state of New York.

Weights	**Avg. Distance to**			**Local Bias,**	
Funds - Firms	**Holding**	**Market**	**Diff.**	**%**	**t-stat**
All States					
Equal-Equal	1,766.31	1,807.46	41.15	2.33	8.22
Equal-Value	1,766.31	1,833.61	67.30	3.81	13.66
Value-Equal	1,709.65	1,729.80	20.15	1.18	23.49
Value-Value	1,709.65	1,774.10	64.45	3.77	30.45
Excluding NY					
Equal-Equal	1,875.78	1,956.52	80.74	4.30	11.59
Equal-Value	1,875.78	1,968.24	92.46	4.93	13.57
Value-Equal	1,805.83	1,845.77	39.94	2.21	24.53
Value-Value	1,805.83	1,876.63	70.80	3.92	27.19

Table 4: Size and leverage as determinants of local bias

This table reports OLS coefficient estimates and standard errors (clustered by stock-fund and quarter) using $LB^{i}_{f,,t}$ as the dependent variable, using quarterly observations. The sample period is from first quarter of 1999 to fourth quarter 2012. *Size* is a natural logarithm of *Market Capitalization*. *Leverage* is a ratio of total liabilities to total assets.
Figures marked with ***, **, * are significant at the 1%, 5% and 10% respectively.

	All States	NY	Excl. NY
$Size^{i}_{t}$	-0.0110***	-0.0421***	0.0025
	(0.0021)	(0.0035)	(0.0020)
$Leverage^{i}_{t}$	0.1084***	0.1555***	0.0773***
	(0.0095)	(0.0167)	(0.0097)
$LB^{i}_{f,t-1}$	0.8316***	0.8306***	0.8311***
	(0.0116)	(0.0181)	(0.0117)
Constant	-0.2267***	-0.0855***	-0.2794***
	(0.0182)	(0.0214)	(0.0200)
R2	0.5323	0.5254	0.5402
N	2,554,544	946,442	1,608,102

Table 5: Sorting analysis of local bias

This table reports arithmetic *Mean* $\Delta W_{f,t}^{i}$ grouped and sorted by distance quintiles. The outer bounds of the quintiles are inclusive, the inner bounds, except for zero, are exclusive.

Distance groups	Mean $\Delta W^{i}_{f,t}$
0 - 100 km	0.160
100 - 500 km	0.031
500 - 1,000 km	0.004
> 1,000 km	-0.019

Table 6: ANOVA test of difference in means

This table reports the results of ANOVA test of differences in means of *Delta Weight* among different *Distance* groups. Figures marked with ***, **, * are significant at the 1%, 5% and 10% respectively.

	Df	Sum Sq	Mean Sq	F value	p-value
Distance groups	3	7,534	2,511	273	0.0000***
Residuals	2,692,608	24,800,107	9.2		

Table 7: Tukey HSD test

This table reports the results of Tukey HSD test. *Distance groups* are presented in kilometers. Standard errors are clustered at stock-fund and quarter levels. Outer bounds of distance intervals are inclusive, while inner bounds are exclusive.
Figures marked with ***, **, * are significant at the 1%, 5% and 10% respectively.

Distance groups	Mean diff.		St. Error	adj. p-value
[100-500 km] - [0 - 100 km]	-0.1290	***	0.0277	0.0000
[500-1,000 km] - [0 - 100 km]	-0.1556	***	0.0291	0.0000
[1,000-4,500 km] - [0 - 100 km]	-0.1791	***	0.0243	0.0000
[500-1,000 km] - [100 - 500 km]	-0.0266		0.0204	0.1928
[1,000-4,500 km] - [100 - 500 km]	-0.0501	***	0.0157	0.0014
[1,000-4,500 km] - [500 - 1,000 km]	-0.0236		0.0166	0.1563

Table 8: Stock weight divergence and distance between hedge funds and portfolio companies

This table reports OLS coefficient estimates and standard errors (clustered by stock-fund and quarter) using $\Delta W^{i}_{f,,t}$ as the dependent variable, using quarterly observations. The sample period is from first quarter of 1999 to fourth quarter 2012. *Log* $(D^{i}_{f,t}/D^{i}_{xf,t})$ is a natural logarithm of the ratio of *Distance* between fund *f* and company *i* to the mean *Distance* between all other funds in the sample holding this stock and company *i* . *Size* is a natural logarithm of market capitalization of a portfolio company. *BM* is *Book-to-Market* ratio of a portfolio company. *Momentum* is the compounded return of the stock for the four quarters preceding the quarter of observation. Column 1 reports the results for the full sample. Column 2 presents the results for a sub-sample of 1,000 largest stocks in CRSP database in each quarter.
Figures marked with ***, **, * are significant at the 1%, 5% and 10% respectively.

	Full Sample	**1,000 stocks**
	(1)	**(2)**
Log ($D^{i}_{f,t}/D^{i}_{xf,t}$)	-0.0129***	-0.0134***
	(0.0012)	(0.0013)
$Size^{i}_{t}$	0.0068***	0.0028**
	(0.0009)	(0.0014)
BM^{i}_{t}	0.0117***	0.0121***
	(0.0029)	(0.0041)
$Momentum^{i}_{t}$	-0.0108***	-0.0106**
	(0.0032)	-0.0044
$\Delta W^{i}_{f,t-1}$	0.8271***	0.8273***
	(0.0091)	(0.0093)
Constant	-0.0599***	-0.0211
	(0.0091)	(0.0143)
R2	0.5395	0.5316
N	2,411,829	1,451,664

Table 9: Stock weight divergence and distance between hedge funds and portfolio companies (Portfolio size sub-samples)

This table reports OLS coefficient estimates and standard errors (clustered by stock-fund and quarter) using $\Delta W^{i}_{f,,t}$ as the dependent variable, using quarterly observations. The sample period is from first quarter of 1999 to fourth quarter 2012. *Log* $(D^{i}_{f,t}/ D^{i}_{xf,t})$ is a natural logarithm of the ratio of *Distance* between fund *f* and company *i* to the mean *Distance* between all other funds in the sample holding this stock and company *i* . *Size* is a natural logarithm of market capitalization of a portfolio company. *BM* is *Book-to-Market* ratio of a portfolio company. *Momentum* is the compounded return of the stock for the four quarters preceding the quarter of observation. Column 1 reports the results for the sub-sample of *Portfolios* larger than the median *Portfolio* in the quarter of observation. Column 2 presents the results for a sub-sample of *Portfolios* equal or below the median. Figures marked with ***, **, * are significant at the 1%, 5% and 10% respectively.

	Portfolio above median (1)	**Portfolio equal or below median** (2)
Log ($D^{i}_{f,t}/D^{i}_{xf,t}$)	-0.0060***	-0.0256***
	(0.0011)	(0.0024)
$Size^{i}_{t}$	0.0080***	-0.0073***
	(0.0015)	(0.0017)
BM^{i}_{t}	0.0262***	-0.0019
	(0.0049)	(0.0058)
$Momentum^{i}_{t}$	-0.0029)	-0.0119
	(0.0052)	-0.0077
$\Delta W^{i}_{f,t-1}$	0.7543***	0.8328***
	(0.0162)	(0.0093)
Constant	-0.2350***	0.1895***
	(0.0132)	(0.0178)
R2	0.5500	0.5293
N	1,200,335	1,211,494

Table 10: Piecewise linear regression

This table reports OLS coefficient estimates and standard errors (clustered by stock-fund and quarter) of the piecewise linear regression using $\Delta W^{i}_{f,,t}$ as the dependent variable, using quarterly observations. The break point for the regression is set at *Log* $(D^{i}_{f,t}/ D^{i}_{xf,t})$ =0.The sample period is from first quarter of 1999 to fourth quarter 2012. *Log* $(D^{i}_{f,t}/ D^{i}_{xf,t})$ is a natural logarithm of the ratio of *Distance* between fund *f* and company *i* to the mean *Distance* between all other funds in the sample holding this stock and company *i* . *Size* is a natural logarithm of market capitalization of a portfolio company. *BM* is *Book-to-Market* ratio of a portfolio company. *Momentum* is the compounded return of the stock for the four quarters preceding the quarter of observation.
Column 1 reports the results for the full sample. Column 2 presents the results for a sub-sample of 1,000 largest stocks in CRSP database in each quarter.
Figures marked with ***, **, * are significant at the 1%, 5% and 10% respectively.

	Full Sample (1)	**1,000 stocks (2)**
Log $(D^{i}_{f,t}/D^{i}_{xf,t}) \leq 0$	-0.0104***	-0.0105***
	(0.0013)	(0.0014)
Change in slope Log $(D^{i}_{f,t}/D^{i}_{xf,t}) > 0$	-0.0185***	-0.0272***
	(0.0062)	(0.0084)
$Size^{i}_{t}$	0.0068***	0.0031**
	(0.0009)	(0.0014)
BM^{i}_{t}	0.0118***	0.0122***
	(0.0029)	(0.0041)
$Momentum^{i}_{t}$	-0.0108***	-0.0107**
	(0.0032)	(0.0044)
Lag $\Delta W^{i}_{f,t}$	0.8271***	0.8273***
	(0.0091)	(0.0094)
Constant	-0.0549***	-0.0166
	(0.0090)	(0.0144)
R2	0.5395	0.5316
N	2,411,829	1,451,664

Table 11: Raw returns of Local and Distant portfolios (annualized)

This table reports average annualized raw returns of *Local* and *Distant* portfolios, as well as the appropriate t-statistics. The cut-off for locality definition is set at *100km*. The analysis results for separate funds are averaged using equal weights (*Equal*) and *Portfolio* size (*Value*). *Quintiles* are quintiles of weight of local portfolios. *Quintile ranges* are expressed in percentages of total *Portfolio*. The results are reported for 1999-2005 and 2006-2012 sub-samples, as well as for the full sample 1999-2012.

Panel A. Equal weights

Local portfolio quintiles	Quintile range, % of Portfolio	1999-2005				2006-2012				1999-2012			
		R^{Local}	$R^{Distant}$	Diff	t-stat	R^{Local}	$R^{Distant}$	Diff	t-stat	R^{Local}	$R^{Distant}$	Diff	t-stat
Q1	[0.0, 3.55]	6.725	7.015	-0.290	0.138	4.854	3.357	1.497	0.908	5.578	4.772	0.806	0.622
Q2	(3.55, 8.28]	8.635	10.313	-1.678	0.876	4.238	5.557	-1.319	0.894	5.852	7.303	-1.451	1.240
Q3	(8.28, 14.4]	9.519	11.279	-1.760	0.968	6.915	7.226	-0.311	0.228	7.859	8.695	-0.836	0.767
Q4	(14.4, 22.7]	6.371	11.445	-5.074	2.997	6.669	7.213	-0.543	0.418	6.566	8.679	-2.113	2.047
Q5	(22.7, 99.2]	2.942	7.429	-4.487	2.162	9.046	7.996	1.050	0.719	6.905	7.797	-0.892	0.746
ALL		**6.871**	**9.461**	**-2.590**	**2.993**	**6.370**	**6.304**	**0.067**	**0.103**	**6.552**	**7.449**	**-0.897**	**1.728**

Panel B. Value weighted

Local portfolio quintiles	Quintile range, % of Portfolio	1999-2005				2006-2012				1999-2012			
		R^{Local}	$R^{Distant}$	Diff	t-stat	R^{Local}	$R^{Distant}$	Diff	t-stat	R^{Local}	$R^{Distant}$	Diff	t-stat
Q1	[0.00, 3.55]	6.982	4.263	2.719	1.455	6.983	3.697	3.285	2.390	6.983	3.869	3.114	2.823
Q2	(3.55, 8.28]	6.572	6.211	0.360	0.214	0.059	2.743	-2.684	2.162	2.085	3.822	-1.737	1.741
Q3	(8.28, 14.4]	4.136	9.686	-5.550	3.462	4.401	4.218	0.182	0.150	4.305	6.195	-1.890	1.950
Q4	(14.4, 22.7]	3.405	8.880	-5.476	3.861	4.047	4.363	-0.315	0.300	3.891	5.458	-1.567	1.851
Q5	(22.7, 99.2]	0.090	6.166	-6.076	3.616	2.502	6.090	-3.588	3.014	1.714	6.115	-4.400	4.531
ALL		**4.409**	**7.187**	**-2.778**	**3.764**	**3.522**	**4.104**	**-0.582**	**1.083**	**3.790**	**5.034**	**-1.244**	**2.870**

Table 12: Risk adjusted returns of Local and Distant portfolios (annualized)
This table reports average annualized *Alphas* of *Local* and *Distant* portfolios, as well as the appropriate t-statistics. The cut-off for locality definition is set at *100km*. The analysis results for separate funds are averaged using equal weights (*Equal*) and *Portfolio* size (*Value*). *Quintiles* are quintiles of weight of local portfolios. *Quintile ranges* are expressed in percentages of total *Portfolio*. *Alphas* are intercepts of respective factor models: the CAPM, Fama and French (FF), and Carhart. The results are reported for 1999-2005 and 2006-2012 sub-samples, as well as for the full sample 1999-2012.

Panel A. Equal weights

Factor	**1999-2005**				**2006-2012**				**1999-2012**			
Model	**Alpha^L**	**Alpha^D**	**Diff**	**t-stat**	**Alpha^L**	**Alpha^D**	**Diff**	**t-stat**	**Alpha^L**	**Alpha^D**	**Diff**	**t-stat**
CAPM	2.981	5.137	-2.156	2.457	0.696	0.504	0.192	0.302	1.828	2.856	-1.028	1.886
FF	-0.324	0.577	-0.901	4.094	0.421	0.002	0.419	1.915	0.527	1.022	-0.495	4.916
Carhart	0.356	0.776	-0.420	3.690	0.353	-0.019	0.371	2.042	0.831	1.085	-0.254	4.619

Panel B. Value weighted

Factor	**1999-2005**				**2006-2012**				**1999-2012**			
Model	**Alpha^L**	**Alpha^D**	**Diff**	**t-stat**	**Alpha^L**	**Alpha^D**	**Diff**	**t-stat**	**Alpha^L**	**Alpha^D**	**Diff**	**t-stat**
CAPM	1.487	3.768	-2.280	2.114	0.936	1.230	-0.294	0.357	1.253	2.541	-1.288	1.904
FF	-1.232	-0.577	-0.655	3.098	0.767	0.822	-0.055	2.070	0.311	1.121	-0.811	4.414
Carhart	-0.766	-0.710	-0.056	2.660	0.716	0.814	-0.098	2.149	0.515	1.061	-0.546	4.120

Table 13: Industrial clustering in states

This table reports the results of the industrial analysis of the investment universe in the states of New York, California and Texas in 1999-2012. The table presents the number of tradable companies in certain sectors based on CRSP universe. The percentage of companies is calculated as number of companies in certain sector divided by the total number of tradable companies located in the state.

New York			California			Texas		
Industry	**# of companies**	**% of companies**	**Industry**	**# of companies**	**% of companies**	**Industry**	**# of companies**	**% of companies**
Holding & Other Investment Offices	303	28.64	Business Services	345	20.27	Oil & Gas Extraction	158	17.03
Business Services	119	11.25	Electronic & Other Electrical Equipment	205	12.04	Business Services	84	9.05
Depository Institutions	73	6.90	Chemicals & Allied Products	173	10.16	Holding & Other Investment Offices	70	7.54
Security & Commodity Brokers, Dealers, Exchanges, etc.	60	5.67	Measuring, Analyzing, & Controlling Instruments	148	8.70	Electric, Gas, & Sanitary Services	43	4.63
Chemicals & Allied Products	56	5.29	Holding & Other Investment Offices	110	6.46	Chemicals & Allied Products	41	4.42

Table 14: Industrial clustering among hedge funds

This table reports the results of the industrial analysis of the actual portfolio holdings of hedge funds in the states of New York, California and Texas in 1999-2012. The table reports total allocation of long equity portfolios of hedge funds to a certain industry. The weight of an industry in a hedge fund portfolio is averaged across all reporting quarters and all funds using weighted average with portfolio sized as weights.

New York		California		Texas	
Industry	**Avg. portfolio weight**	**Industry**	**Avg. portfolio weight**	**Industry**	**Avg. portfolio weight**
Chemicals & Allied Products	10.98	Business Services	11.69	Business Services	9.82
Business Services	10.49	Chemicals & Allied Products	10.30	Electronic & Other Electrical Equipment & Components, Except Computer Equipment	8.77
Communications	7.15	Electronic & Other Electrical Equipment & Components, Except Computer Equipment	8.77	Chemicals & Allied Products	8.23
Electronic & Other Electrical Equipment & Components, Except Computer Equipment	6.42	Communications	7.56	Pipelines, Except Natural Gas	8.14
Oil & Gas Extraction	6.17	Industrial & Commercial Machinery & Computer Equipment	6.75	Oil & Gas Extraction	7.92

Table A1: Comparison of distance measures

This table reports various distance measures calculated for selected pairs of hedge funds and portfolio companies. The pairs were randomly chosen among three groups: long distance (over 1,000 km), medium (between 100 and 500 km), short distance (below 100 km). Distance measures are calculated using spherical law of cosines (*Distance SL*), and Coval and Moskowitz (1999) formula (*Distance CM*). As a benchmark, I report distance obtained from National Hurricane Center. All distances are reported in kilometers.

Fund name	Fund state	Fund lon	Fund lat	Company	Company state	Company lon	Company lat	Distance SL	Distance CM	Distance NHC
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Southeastern Asset Mgmnt	TN	-89.8497	35.1014	Scott Technologies	OH	-81.5089	41.4644	1,015	177	1,014
Zimmer Lucas Partners	NY	-73.9807	40.7653	Allegheny Energy	PA	-79.4398	40.3602	464	98	463
Artis Capital	CA	-122.4088	37.7835	Apple Inc.	CA	-122.0449	37.3180	61	65	61

Table A2: Areas of administrative units

This table reports *Mean*, *Min* and *Max* area of states and counties in the U.S. The data are provided including and excluding administrative units located in Alaska. *Radius* is a radius of a circle that will have the same are as *Mean, Min*, and *Max* areas of administrative units respectively.

	N	**Area, sq.km**			**Radius, km**		
		Mean	**Min**	**Max**	**Mean**	**Min**	**Max**
States	51	192,267.52	176.98	1,699,482.10	247.39	7.51	735.50
States excl. AK	50	162,123.23	176.98	695,407.89	227.17	7.51	470.48
Counties	3,146	78,715.57	2,591.59	145,100.51	158.29	28.72	214.91
Counties excl. AK	3,116	2,600.63	4.74	52,055.44	28.77	1.23	128.72

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VITA

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